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Abstract

We conduct a Learning to Forecast asset pricing experiment where the market impact of individual forecasts evolves endogenously based on the forecasters' past accuracy. We investigate how endogenous impacts affect price stability and mispricing relative to the fundamental price. Our results suggest that endogenous impacts can destabilize markets when impacts are quite sensitive to forecast accuracy: Price dispersion increases compared to the baseline treatment where impacts are constant and independent of forecast accuracy. On the other hand, mispricing can be reduced when markets are relatively stable and impacts are moderately sensitive to forecast accuracy.

Keywords: experimental finance, market impact, expectation formation, asset pricing, learning to forecast

JEL codes: C91, C92, D53, D84, G12

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1 Introduction

Price expectations influence both supply and demand, and therefore have an important role in market outcomes. The relationship between demand and expected price of an asset can typically be described as a positive feedback process. If traders expect an increase in the price of an asset, then their demand for the asset will also increase (to profit from capital gains). This translates to a positive relationship between expected and future prices of assets (see Brock and Hommes, 1998 for a formal model). Recent experimental literature on Learning to Forecast (LtF) games has shown that positive feedback may cause prices to diverge from the fundamental value, resulting in financial bubbles and crashes.[1] Such dynamics may be due to participants whose forecasts about the future price are structurally wrong, but who also have equal impact on aggregate price expectations with respect to other better performing forecasters. We propose an experiment to study whether market expectations lead by the best performing forecasters can enhance price stability in a positive feedback environment.

Our baseline environment follows the LtF experiment by Heemeijer et al. (2009), in which subjects were asked to forecast a one-period ahead price of a risky asset. Market expectations were then calculated as an arithmetic average of subject forecasts. That is, regardless of past performance, each individual forecast was assigned an equal and constant impact (weight) when determining aggregate price expectations. We introduce a competitive aspect to the baseline positive feedback LtF experiment by using the average squared forecast error to assign impact to each individual forecast when determining aggregate price expectations.

Endogenous market impacts may help capture competitive aspects of financial markets. For example, the best-performing money-managers may gain clients while the less successful ones might lose them, potentially leaving the market altogether. Indeed, that is the case according to past literature (Sirri and Tufano, 1998; Choi et al., 2009; and Asparouhova et al., 2015). Successful fund managers attract more money and have a higher impact on the realized market price, which is driven by demand. Our approach also draws on ideas from evolutionary economics (Friedman, 1991). In replicator dynamics competitive forces prioritize successful strategies and eliminate weaker ones. This is similar to increasing the impact of more accurate forecasters (low forecast errors) on prices.

Therefore, in addition to the control treatment with equal and fixed impacts (F), our experimental design includes two additional treatments where we vary the sensitivity of market impacts to past performance. In the *EL* treatment (*Endogenous Low*) impacts are moderately sensitive to accuracy, which leads to some variability in assigned forecaster impacts but does not punish small forecast errors harshly. The other treatment (*EH* -

[1] For a more detailed overview please see Hommes (2011) and the references therein.

Endogenous High) uses strongly sensitive impacts, which penalizes small forecast errors more relative to *EL* and at times leads to only a small set of players having an effect on the market price. By varying impact sensitivity across the three treatments, we aim to study how endogenizing the impact of individual forecasts influences price volatility and mispricing.

The data collected from our experimental sessions shows that the effect of endogenous impacts depends on (i) the nature of market dynamics and (ii) the sensitivity of impacts to forecaster performance. When the market price follows a stable pattern, endogenous impacts reduce mispricing in the *EL* treatment relative to fixed and equal impacts in the *F* treatment. However, when market price dynamics are unstable, impacts that are strongly sensitive with respect to accuracy (*EH*) can amplify the existing price volatility. We do not find any difference in price volatility between the *F* and *EL* treatments. Therefore, our findings suggest that competitive market forces can reduce mispricing in a positive feedback LtF model as long as market expectations are not driven by a few dominant players.

LtF experiments are well suited for studying the formation of expectations. Marimon and Sunder (1993) were among the first to study the effect of expectations on equilibrium outcomes. Our study is motivated by the early LtF experiments of Hommes et al. (2005, 2008), which find persistent deviations from the fundamental price and high level of coordination among individual forecasts. Such patterns also emerge in later LtF experiments with positive feedback, and prove to be robust with respect to large unexpected changes in fundamental value (Bao et al., 2012), additional trading decisions (Bao et al., 2017) and group size (Bao et al., 2016, Hommes et al., 2018).[2] To the best of our knowledge, we are the first to study the effect of endogenous impacts on aggregate price expectations.

The rest of the paper is organized as follows: Section 2 describes the price formation process and formalizes our predictions, Section 3 summarizes the laboratory procedures and Section 4 presents our results on price volatility, mispricing and coordination. We conclude with a brief discussion in Section 5. Appendix A includes the complete series of plots from our experimental sessions. Appendix B shows the results of the forecasting rules estimated using subject data, and finally Appendix C presents the instructions used in our sessions with endogenous impacts.

[2] There are also LtF experiments with negative feedback, using the cobweb model. See Hommes et al. (2007), Bao et al. (2012) and Bao et al. (2013). Under negative feedback, there is less coordination across forecasts. However, the market price tends to converge quickly to the fundamental value.

2 Asset pricing model with endogenous impacts

Our environment closely follows the standard LtF asset pricing model with one-period-ahead forecasting. In this model mean-variance investors allocate their wealth to risk-free and risky assets. The demand for the risky asset depends on the investor price expectations for the risky asset. The market price adjusts based on the aggregate excess demand for the risky asset, resulting in a positive relationship between the average expected price and the realized market price. For a formal derivation see Heemeijer et al. (2009) or Brock and Hommes (1998).

The price adjustment process is formalized as

$$p_t = \frac{1}{1+r}(\bar{p}_t^e + y) + \varepsilon_t, \quad \varepsilon \sim N(0, 1/4), \tag{1}$$

where p_t denotes the price of the risky asset in period t, r represents the risk-free interest rate, y is the expected dividend paid by the risky asset, ε_t is a small demand/supply shock and $\bar{p}_t^e$ is the weighted average of the price expectations of N subjects in our experiment, or

$$\bar{p}_t^e = \sum_{h=1}^{N} \omega_{h,t} p_{h,t}^e, \tag{2}$$

where $p_{h,t}^e$ is the price expectation of agent h in period t. In the standard LtF model average expectations are calculated using equal weights, such that $\omega_{h,t} = \frac{1}{N}$. In contrast, in the present study we assume that the impacts evolve endogenously over time, based on past forecast accuracy. We motivate the use of endogenous impacts as follows. In our experiment, subjects play the role of advisors to the investors, whose investment decision, and therefore market demand, is driven by the price forecasts of the advisors. Furthermore, we assume that investors have a tendency to follow the recommendation of the most accurate forecasters, as determined by the last m periods, or most recent (short-term) forecast history.

More formally, the performance of each advisor is measured by the average squared forecast error $\bar{e}_{h,t-1}$ over the last m periods, while the impacts are given by the discrete choice probabilities,[3]

$$\omega_{h,t} = \frac{\exp(-\beta \bar{e}_{h,t-1})}{\sum_{i=1}^{N} \exp(-\beta \bar{e}_{i,t-1})}, \tag{3}$$

where $\bar{e}_{h,t-1} = \frac{1}{m}\sum_{k=1}^{m}(p_{t-k} - p_{h,t-k}^e)^2$ and $\beta \geq 0$ is the intensity of choice, which mea-

[3] The discrete choice model is frequently used to model choices between strategies in this asset-pricing framework, see Brock and Hommes (1998) and Anufriev and Hommes (2012) for example. For further details on the discrete choice model see McFadden (1981).

sures how sensitive investors are to advisor performance.[4] When $\beta = 0$, the impact of an individual expectation is not affected by forecaster accuracy. That is, $\omega_{h,t} = \frac{1}{N}$ and the environment is then identical to the one in Heemeijer et al. (2009). At the other extreme, when $\beta = \infty$, the price forecast of the most accurate advisor has an impact of one.[5] In such a case, the advisor with the impact $\omega_{h,t} = 1$ drives the market because all investors will follow her advice. For the intermediate cases, impacts are strictly between zero and one, with more accurate advisors having greater impact on the market price relative to less accurate advisors.

In this experiment we study the effect of endogenous impacts on price stability and mispricing by varying the sensitivity parameter β. For our control treatment (F) we use fixed impacts and set $\beta = 0$. To study the effect of the sensitivity parameter, we focus on two distinct values: (i) $\beta = 0.1$ for the Endogenous Low (EL) treatment and (ii) $\beta = 5$ for the Endogenous High (EH) treatment.[6] In EL, the penalty for forecast errors is relatively mild compared to the EH treatment. In the latter, forecast errors can heavily reduce the impact of a forecaster in the determination of the market price. Therefore, in EH the market can be driven by a small subset of players.

2.1 Predictions

The effect of endogenous impacts on price dynamics is closely related to the existing stability of a market. For example, endogenous impacts can be stabilizing, when the market is already relatively stable. When the average price expectations are close to the fundamental value $p^f = \frac{y}{r}$ (which corresponds to the rational expectations equilibrium -REE- of the model), then subjects with similar forecasts have a higher impact assigned to their forecasts, relative to those who deviate. Therefore, fundamentalists will have a greater impact on market price and we expect to observe faster convergence to the equilibrium under endogenous impacts.

On the other hand, endogenous impacts can also be destabilizing. When individual forecasts are far above the fundamental price, the market price will be significantly different from the fundamental value. In such case, a fundamental forecast will result in lower impact and price dynamics will mainly be driven by non-fundamental forecasters. Hence, stabilizing factors (such as fundamental forecasts) have a lower impact on price dynamics in this case. Based on the above arguments, we formulate the following hypotheses:

[4] We elaborate further on our choice of performance measure in the Discussion.

[5] In the case of multiple best performers, the best players will have equal impact on the market price while other forecasters will have no impact.

[6] To determine appropriate treatment values for β we ran numerical simulations with the forecasting rules estimated in Hommes et al. (2005). When $\beta = 0.1$, we could observe moderate impact dispersion during the initial periods, with impacts becoming more equal in later periods. In contrast, when $\beta = 5$ we found a large variability across all periods.

Hypothesis 1A: *Endogenous impacts reduce price volatility when markets are stable.*
We determine the impact for each individual forecast relative to the market price, which is driven by expectations. When average expectations are rational, fundamental forecasters are deemed more accurate and their forecasts have a larger impact. Due to such feedback, endogenous impacts can further stabilize a relatively stable market.

Hypothesis 1B: *Endogenous impacts amplify price volatility when markets are unstable.*
Similarly, when average expectations deviate from the REE, fundamental forecasts are penalized because they deviate from those of an average forecaster. Such market is driven by non-fundamental forecasters who have a greater impact on the market price.

Hypothesis 2A: *Endogenous impacts reduce mispricing in stable markets.*
When average expectations are rational, forecasts close to the fundamental value become more accurate relative to market price. Therefore, such forecasts have larger impact and convergence to REE is faster.

Hypothesis 2B: *Endogenous impacts increase mispricing in unstable markets.*
When average expectations deviate from REE, fundamental forecasts have less impact, and therefore the market price moves away from the fundamental price.

To evaluate our predictions, we conduct a laboratory experiment, which we describe in greater detail in the following section.

3 Laboratory Procedures

The experiment was conducted in the Learning and Experimental Economics Projects Laboratory (LEEPS) at the University of California, Santa Cruz; Colby Economics Learning Laboratory (CELL) at Colby College and Monash Laboratory for Experimental Economics (MonLEE) at Monash University. Participants included undergraduate students from all fields and were recruited online via ORSEE (Greiner, 2015) and SONA (Monash). Subjects were assigned to participate in one of three treatments: (i) Fixed (F), (ii) Endogenous Low (EL), or (iii) Endogenous High (EH). In total 174 subjects participated in this experiment, across 29 between-subjects sessions (9 F sessions, 10 EL sessions, and 10 EH sessions).[7] Table 1 provides an overview of all sessions conducted across the three

[7] While we planned to have 10 F sessions, one session crashed in period 26 due to server issues. Since the results of our F groups are quite similar to previous LtF experiments, we decided to not run additional sessions.

Treatment (Lab)	Groups	Payoff (USD, no show-up fee)
F (UCSC)	4	7.4
F (Colby)	3	7.1
F (Monash)	2	7.5
EL (UCSC)	4	7.2
EL (Colby)	3	7.7
EL (Monash)	3	7.4
EH (UCSC)	5	6.9
EH (Colby)	2	7.6
EH (Monash)	3	7.5
Total	29	7.4 (mean)

Table 1: Sessions overview

laboratories.

In each experimental asset market $N = 6$ subjects were asked to forecast the one-period ahead price for 50 consecutive periods. Participants were informed that their job was to act as advisors to investors, whose demand for assets affects market prices.[8] Subjects also received qualitative information about the market. While they were informed about the positive relationship between price expectations and market price, they were not provided with price dynamics as specified by equation (1).

In the *EL* and *EH* treatments subjects were told that their impact on the market price may vary according to past performance. Specifically, the instructions state that "*traders have a tendency to use the advice of advisors whose forecasts have been more accurate in the recent past. The effect that an advisor has on the market is therefore higher when his/her forecasts are more accurate because more traders will follow his/her advice.*" However, we did not provide the subjects with the details about how impacts are calculated, as described by equation (3). Therefore, the subjects did not know the exact parameters used, such as the value $m = 3$ in determining forecast accuracy.[9] Following Heemeijer et al. (2009), the remaining market parameters $\{y, r\}$ were set to be $\{3, 0.05\}$, and resulted in a fundamental price of $p^f = 60$.

Each session began with the reading of the instructions, followed by five control questions to make sure that participants understood the task. Next, subjects were presented an interface, depicted in Figure 1, and asked to submit a one-step ahead forecast. This process was repeated for a total of 50 periods. Subjects had limited time to submit their forecasts.[10] When a subject did not submit a forecast on time, then she was disregarded from the calculations in that period.[11] Every period, subjects were provided with the fol-

[8] See Appendix C for detailed instructions used in *EL* and *EH*. Instructions for the baseline treatment *F* are available upon request.

[9] In the first period forecasts had equal impacts. In period 2, impacts were determined using the quadratic forecast error from period 1 only while in period 3 the average of the quadratic forecast errors over the previous two periods was considered.

[10] 1 minute in each of the first 10 periods and 45 seconds in each of the later periods.

[11] That is, average price expectations are calculated over those subjects that did submit a forecast on time.

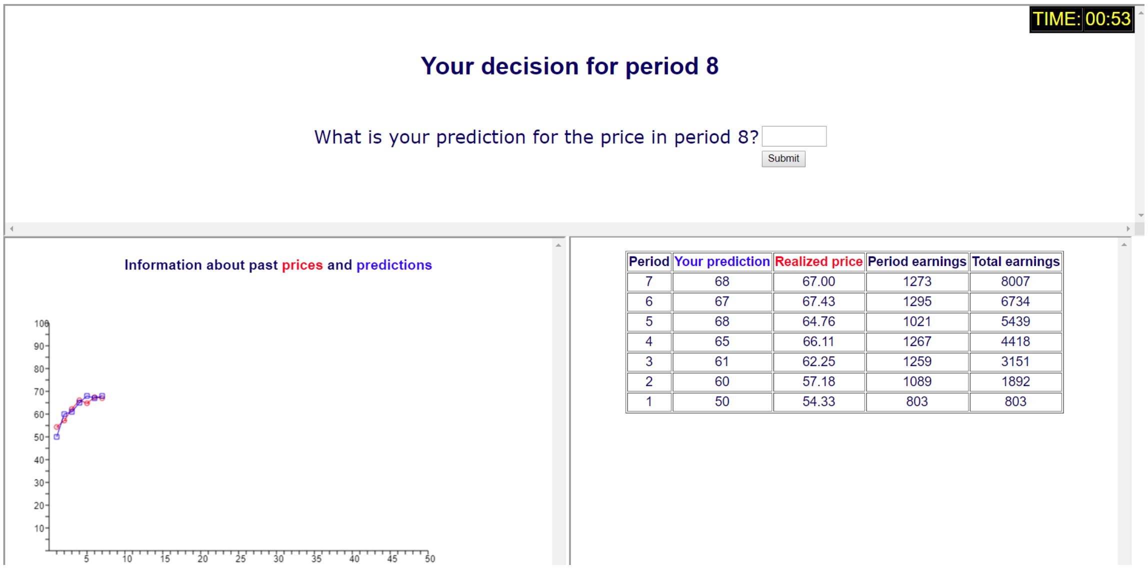


Figure 1: Screenshot of the experimental interface

lowing time-series: (i) the market price, and (ii) their own forecasts. Subjects also had access to updated information on their earnings. Note, however, that subjects were not informed about their current or past market impacts in any of the treatments. The earning (in period t) of each subject was calculated using the quadratic forecast error:

$$\pi_{h,t} = \max\left\{1300 - \frac{1300}{49}(p_t - p^e_{h,t})^2, 0\right\}. \tag{4}$$

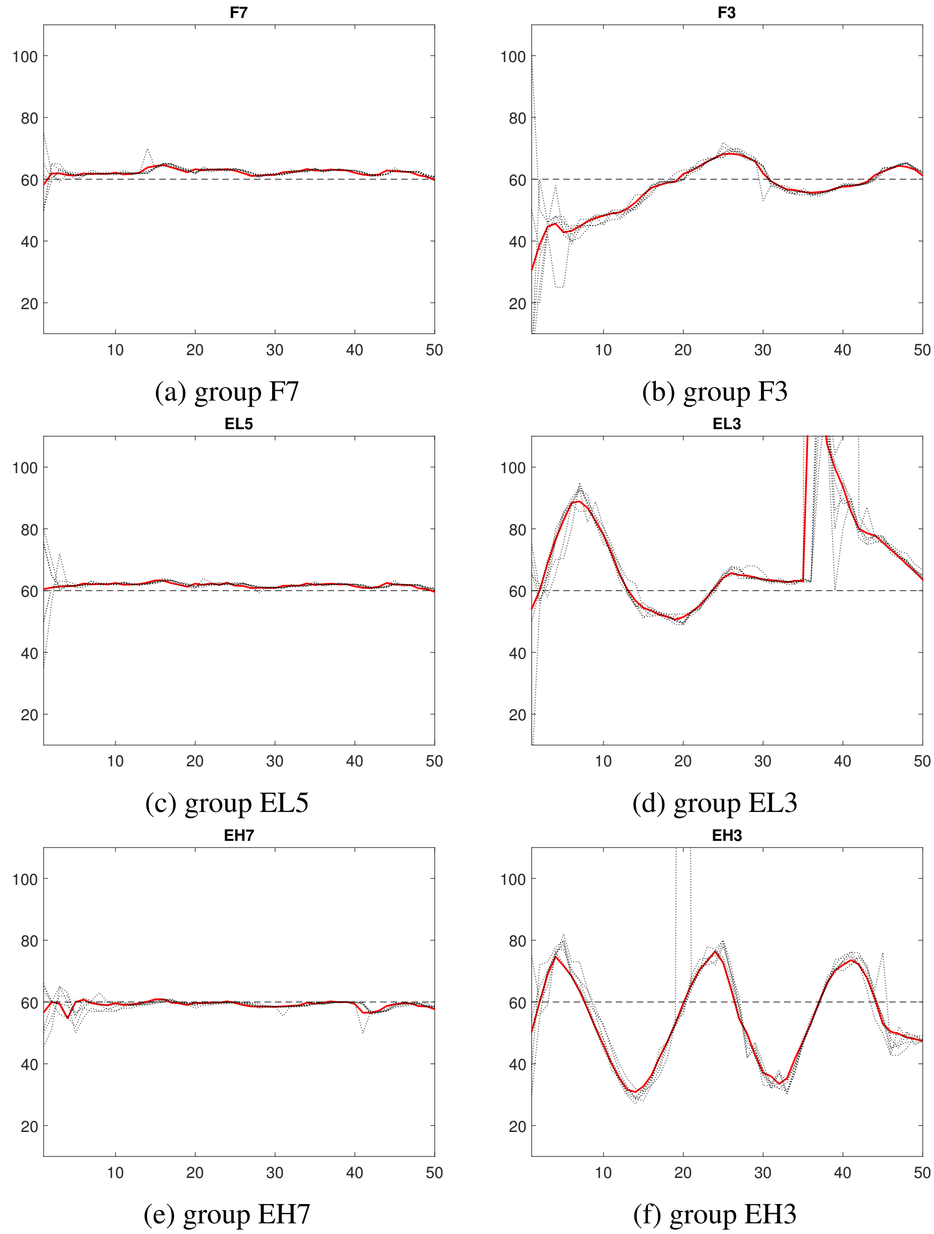
We constrained earnings to a lower bound of zero in order to avoid losses in the laboratory environment. The points earned over the 50 periods were added up and converted to cash at the end of the session using the exchange rate of 1 USD per 8125 points in UCSC and Colby and 1 AUD per 5932 points in Monash. Each subject also received a show-up fee of either USD 7 (UCSC and Colby) or AUD 10 (Monash). The average payoff was \$7.4, excluding the show-up fee.[12] The experimental sessions lasted less than one hour on average.

4 Results

We begin the discussion of our results with some examples of price time-series found across the three treatments (F, EL, and EH). The left-hand side of Figure 2 shows examples of stable markets while the right-hand side shows some representative unstable markets from our sessions. Stability, or the lack thereof, is shown relative to the fun-

Impacts are normalized to add up to 1.

[12] To calculate payoffs across two countries we used the exchange rate of AUD 1.37 per 1 USD.



(a) group F7 (b) group F3

(c) group EL5 (d) group EL3

(e) group EH7 (f) group EH3

Figure 2: A subset of price market results by treatment (rows) and stability (columns).

damental value, which is depicted as a horizontal line at 60 in each plot.[13] Solid lines correspond to the market price while dotted lines represent subjects' forecasts.

For the most part, market prices do not appear to deviate too far from the fundamental price, even in unstable groups in F and EL treatments (panels (a)-(d)).[14] In contrast, insta-

[13]See Appendix A for the figures from all 29 groups. Beside price plots we also report the time series of impacts for EL and EH groups.

[14]We should note that in the unstable example of the EL treatment (panel (d)), the deviation from the fundamental value in the later periods appears to be due to a typo. A subject whose forecast was assigned a relatively high impact entered a forecast of 602.8 in period 36. This caused a large price jump, breaking the pattern of what appeared to be an oscillating convergence to the fundamental price until period 36. That subject's impact dropped to zero for the subsequent periods. A similar phenomenon occurred in group $EL8$ as well.

		groups 1	2	3	4	5	6	7	8	9	10
std	**F**	2.82	7.03	5.01	2.65	0.87	4.64	0.99	3.38	2.80	-
	EL	1.03	4.54	20.14	2.34	0.73	3.35	2.93	31.36	5.42	0.88
	EH	12.55	1.25	13.96	2.75	10.48	0.92	0.96	2.26	8.33	0.90
range	**F**	11.37	24.38	19.33	11.42	3.57	20.38	4.91	11.95	12.07	-
	EL	4.79	15.11	95.94	8.10	3.74	15.11	13.98	101.43	20.69	4.12
	EH	53.31	5.47	45.51	9.52	34.00	3.05	4.36	10.07	35.99	4.16
RADm	**F**	0.04	0.09	0.07	0.04	0.01	0.06	0.01	0.04	0.03	-
	EL	0.01	0.07	0.2	0.03	0.01	0.04	0.04	0.32	0.07	0.01
	EH	0.18	0.02	0.23	0.04	0.16	0.01	0.01	0.03	0.1	0.01

Table 2: Standard deviation of market price (std), price range and relative absolute deviation from the mean price (RADm) for each group.

bility in EH appears to be qualitatively different relative to the two other treatments. Unstable groups in EH show persistent and large fluctuations as compared to EL and F (and also to other LtF experiments which studied one-period-ahead forecasts, e.g. Heemeijer et al., 2009 and Bao et al., 2017). Panel (f) shows that endogenous impacts may mitigate the effect of typos: In period 20, one subject submitted a forecast of 583 without affecting market dynamics due to the subject's insignificant impact during that period. In general, the data across all three treatments in this study supports findings from previous LtF experiments, suggesting persistent deviations from the fundamental price and a high level of coordination in subjects' expectations.

Before formalizing our first result, it is important to explain how we identify stability, or the lack of it. We focus on three measures: (i) market price standard deviation (std), (ii) market price range, and (iii) relative absolute deviation from the mean price (RADm), defined as $\frac{1}{40}\sum_{t=11}^{50}\frac{1}{\bar{p}}|p_t-\bar{p}|$, where $\bar{p}_t$ is the average price in these 40 periods. Table 2 presents the instability measures, using the data from the last 40 periods in each market to control for learning effects. We rank the groups according to the score for each measure and then aggregate the rankings across all measures. Finally, we compare this ranking with the price time-series to identify the first unstable group.[15] Table 3 gives an overview about the number of stable and unstable groups for each treatment. We end up with a

[15] This process results in the following ranking, beginning with the most stable group: $EL5$, $F5$, $EL10$, $EH10$, $EH6$, $EH7$, $EL1$, $F7$, $EH2$, $EL4$, $EH8$, $EH4$, $F4$, $F9$, $F1$, $EL7$, $F8$, $EL6$, $EL2$, $F6$, $F3$, $EL9$, $F2$, $EH9$, $EH5$, $EH1$, $EH3$, $EL3$, $EL8$. Based on the time series of prices the first nine groups, sorted by treatment ($F5$, $F7$, $EL1$, $EL5$, $EL10$, $EH2$, $EH6$, $EH7$ and $EH10$), are clearly stable. These groups were found to be the most stable according to each of the three instability measures. The next group in our rankings, $EL4$, has substantially lower instability scores than the last stable group, $EH2$. We also categorize the following six groups ($F1$, $F4$, $F9$, $EL4$, $EH4$ and $EH8$) as stable: For the most part, these six groups either (i) show a converging pattern in the second half of the experiment, or (ii) appear to exhibit typos (or experimentation) which cause a small perturbation in an otherwise stable pattern. The remaining 14 groups ($F2$, $F3$, $F6$, $F8$, $EL2$, $EL3$, $EL6$, $EL7$, $EL8$, $EL9$, $EH1$, $EH3$, $EH5$ and $EH9$) are classified as unstable.

	F	EL	EH	total
stable	5	4	6	15
unstable	4	6	4	14

Table 3: Distribution of stable and unstable groups.

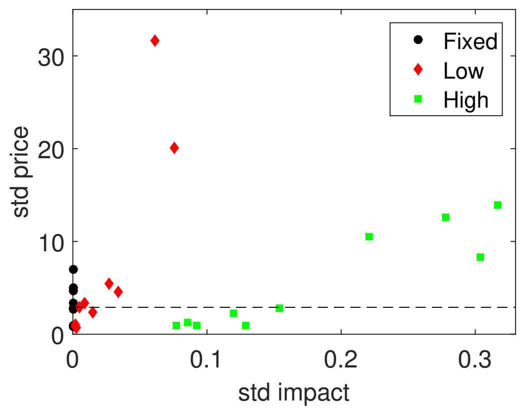


Figure 3: Scatter plot of price dispersion against impact dispersion.

relatively balanced number of stable and unstable groups in each treatment.[16] Using these definitions, we analyze the effect of endogenous impacts on stability and mispricing across the three treatments.

We begin our analysis by looking at the relationship between price dispersion and impact dispersion, as presented in Figure 3.[17] The black circles, red diamonds and green squares correspond to treatments F, EL and EH, respectively. The dashed line separates stable and unstable groups. According to Figure 3, F markets appear to be more homogeneous in terms of price dispersion, relative to the EL and EH markets. Moreover, the stability ranking in footnote 15 shows that F groups generally hold middle ranks whereas the ranks of EL and EH groups are more extreme. This suggests that stable groups in EL and EH tend to be more stable than F groups and the opposite holds for unstable groups. Let us also remark that the very high price dispersion in two EL groups is caused by typos.

If we concentrate on stable groups only, then we find that there is no substantial difference in (i) the number of stable groups across treatments (five in F, four in EL and six in EH)[18] and (ii) the price dispersion of stable groups. Therefore, endogenous impacts do not appear to have an effect on stability for this sub-sample. Notice that in each treatment, the dispersion of impacts among stable groups is lower than in unstable groups. In par-

[16]We do not observe systematic differences between locations. Stable as well as unstable markets occur in all three labs.

[17]Price dispersion is measured as the standard deviation of the market price over the last 40 periods. To calculate impact dispersion we use the standard deviation of impacts for each period separately and consider the average of these standard deviations over the last 40 periods.

[18]The differences are larger if we focus only on the first nine clearly stable groups: two in F, three in EL and four in EH. However, these differences are not statistically significant.

	F vs. EL	F vs. EH	EL vs. EH	F vs. E
all groups	0.991	0.435	0.988	0.632
stable	0.202	0.359	0.586	0.189
unstable	0.587	0.018	0.236	0.128

Table 4: P-values for the Kolmogorov-Smirnov test comparing treatments using the standard deviation of prices.

ticular, the standard deviation of impacts for stable groups in EL is close to zero. When we restrict our sample to unstable groups only, we find price dispersion to increase under endogenous impacts. For example in EH, the standard deviation of price is consistently around ten in unstable groups, compared to less than five for stable groups. This suggests that endogenous impacts may have a destabilizing effect relative to our control treatment F, and leads us to our first formal result.

Result 1. *Endogenous impacts do not affect price dispersion in stable groups. In unstable groups, endogenous impacts with high sensitivity are destabilizing.*

While endogenous impacts do not affect the number of stable markets or price dispersion within markets when the market is already relatively stable, in unstable markets price dispersion is significantly larger when β is high (EH treatment).

We also compare price dispersion across the three treatments using a Kolmogorov-Smirnov test.[19] Table 4 presents the p-values.[20] The first row shows that there are no stability differences between treatments when we use all groups. Similarly, when we constrain the sample to stable groups only, we do not find differences in stability. Therefore, our results do not support Hypothesis 1A and we can conclude that stable groups are not more stable under endogenous impacts. If we look at the third row of Table 4, we find evidence of greater price dispersion in EH groups relative to F groups ($p = 0.018$). In this case, price dispersion increases by 126 percent.[21] Therefore, we find some evidence in support of Hypothesis 1B and can conclude that unstable groups become more unstable under endogenous impacts when β is high enough.

To evaluate the extent of mispricing across our three treatments, we adopt a standard bubble indicator (Stöckl et al., 2010), the relative absolute deviation from the fundamental price (RAD) or $\frac{1}{40}\sum_{t=11}^{50}\frac{|p_t - 60|}{60}$. Table 5 reports the RAD values for each group, while Figure 4 illustrates the relationship between mispricing, using RAD values, and impact

[19]The other two instability measures discussed in the beginning of this section lead to similar conclusions.

[20]In line with our hypotheses, we use one-sided tests to compare treatment F with EL, F with EH, and F with E (EL and EH pooled) separately for stable and unstable groups. We use two-sided tests to compare EL with EH groups and in all tests where we do not distinguish stable and unstable groups. As observations correspond to groups, the number of observations can be found in Table 3.

[21]For unstable groups the average standard deviation is 5.01 in treatment F whereas it is 11.33 in EH.

	groups									
	1	2	3	4	5	6	7	8	9	10
F	**0.04**	0.16	0.07	**0.08**	**0.06**	0.09	**0.04**	0.07	**0.03**	-
EL	**0.02**	0.07	0.23	**0.05**	**0.03**	0.04	0.04	0.29	0.09	**0.02**
EH	0.18	**0.07**	0.23	**0.04**	0.16	**0.01**	**0.02**	**0.05**	0.11	**0.03**

Table 5: Mispricing (RAD) in each group. Stable groups are denoted with bold values.

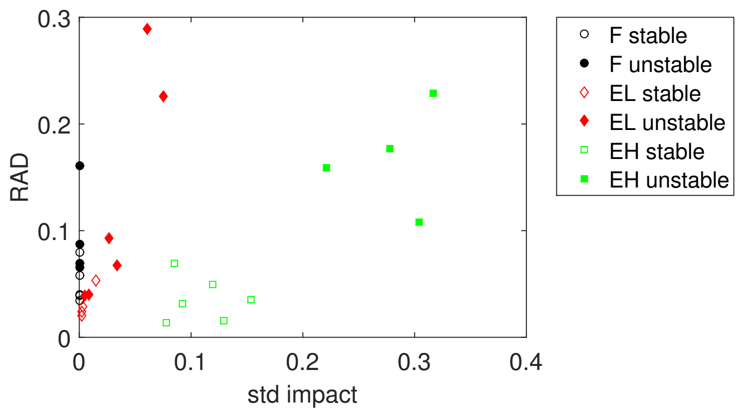


Figure 4: Scatter plot of mispricing (RAD) against impact dispersion.

dispersion. Empty shapes denote stable groups across different treatments, while shaded shapes represent unstable groups. We use different colors to denote our treatments, where black, red and green correspond to F, EL, and EH, respectively.

If we focus only on stable groups, we find that EL leads to less mispricing relative to F. Treatment EH also seems to result in lower RAD values compared to F, but the difference is less pronounced. For unstable groups, we do not observe a clear difference between F and EL groups. However, the data suggests that relative to F, the EH groups exhibit greater mispricing. To formally test these observations, we perform Kolmogorov-Smirnov tests.

Result 2. *In stable groups, mispricing is lower under endogenous impacts compared to fixed impacts.*

We find that in stable groups endogenous impacts help reduce the extent of mispricing. Unstable groups, on the other hand, exhibit similar levels of mispricing across all treatments. Table 6 summarizes the p-values for the Kolmogorov-Smirnov tests. Similar to our results for stability, the test does not indicate any differences between treatments when we use all groups in our analysis. If we restrict our sample to stable groups, we find that mispricing is lower (at the 10 percent significance level) in EL relative to F ($p = 0.082$), and in the pooled endogenous treatment E relative to F ($p = 0.091$). In case of EL, mispricing is reduced by about 2 percentage points compared to F and the improvement is about 1.5

	F vs. EL	F vs. EH	EL vs. EH	F vs. E
all groups	0.787	0.787	0.988	0.632
stable	0.082	0.256	0.799	0.091
unstable	0.587	0.105	0.236	0.314

Table 6: P-values for the Kolmogorov-Smirnov test comparing mispricing (RAD) across treatments.

percentage points in the merged endogenous treatment.[22] We do not find a significant difference across treatments when we analyze only unstable groups. Therefore, our findings suggest evidence in support of Hypothesis 2A but not for Hypothesis 2B.

As noted earlier, the LtF literature has found substantial evidence for coordination of expectations. Therefore, as our next step, we analyze whether endogenous impacts affect the coordination of subjects' forecasts, using the forecast error decomposition proposed by Hommes et al. (2005). The average individual error (IE) for a group is defined as $\frac{1}{240}\sum_{h,t}\left(p^e_{h,t}-p_t\right)^2$, where p_t is the price in period t ($t = 11,\ldots,50$) and $p^e_{h,t}$ is subject h's ($h = 1,\ldots,6$) price forecast for period t. Thus, IE is the average of the quadratic forecast errors across time and subjects, belonging to a particular group. This error can be decomposed into two parts, the average dispersion error (DE) and the average common error (CE). DE measures how close individual forecasts are to the group average and can be written as $\frac{1}{240}\sum_{h,t}\left(p^e_{h,t}-\bar{p}^e_t\right)^2$, where $\bar{p}^e_t$ is the average price forecast for period t. CE, computed as $\frac{1}{40}\sum_{t}(\bar{p}^e_t-p_t)^2$, measures the group average forecast error.[23]

Since the terms above use squared errors, they are quite sensitive to outliers. For this reason, we remove them in order to obtain a more accurate measure of coordination. A forecast is considered an outlier if it deviates too much from the latest price, taking into account the direction of the price change. More specifically, if the price was increasing in the previous period, then the forecast for the current period will be considered an outlier if it is at least (i) 25% higher than the previous price, or (ii) 5% lower than the previous price. Formally, $p^e_{h,t}$ is an outlier if $p^e_{h,t} \notin (0.95p_{t-1}, 1.25p_{t-1})$. Similarly, if the price in the previous period was decreasing, then the forecast for the current period will be considered an outlier if $p^e_{h,t} \notin (0.75p_{t-1}, 1.05p_{t-1})$. Finally, if the price did not change in the previous period, then a forecast will considered to be an outlier if $p^e_{h,t} \notin (0.75p_{t-1}, 1.25p_{t-1})$.[24]

[22]The exact values of mispricing for the three treatments in question are 0.0504 in *F*, 0.0315 in *EL* and 0.0342 in *E*.

[23]When someone fails to submit a forecast in the time given, that 'forecast' is not considered in the average individual and dispersion errors (i.e. the error is entered as zero and we divide by a number less than 240). The definition of the dispersion error is also slightly modified.

[24]Using this rule we remove 1.9%, 1.0% and 1.0% of the forecasts in treatments *F*, *EL* and *EH*, respectively.

group	individual error	dispersion error	common error
F1	**2.05**	**0.09 (4%)**	**1.95 (95%)**
F2	9.04	2.39 (26%)	6.65 (74%)
F3	1.31	0.89 (68%)	0.42 (32%)
F4	**1.97**	**0.21 (11%)**	**1.75 (89%)**
F5	**0.67**	**0.13 (19%)**	**0.54 (81%)**
F6	5.30	0.73 (14%)	4.57 (86%)
F7	**0.58**	**0.27 (47%)**	**0.31 (53%)**
F8	1.55	1.20 (77%)	0.35 (23%)
F9	**0.67**	**0.24 (36%)**	**0.43 (64%)**
EL1	**0.34**	**0.04 (12%)**	**0.30 (88%)**
EL2	2.67	0.76 (28%)	1.90 (71%)
EL3	162.85	3.74 (2%)	159.12 (98%)
EL4	**1.06**	**0.25 (24%)**	**0.81 (76%)**
EL5	**0.38**	**0.08 (21%)**	**0.30 (79%)**
EL6	0.49	0.13 (27%)	0.36 (73%)
EL7	2.37	0.21 (9%)	2.17 (92%)
EL8	180.96	4.28 (2%)	176.68 (98%)
EL9	3.62	0.72 (20%)	2.90 (80%)
EL10	**0.36**	**0.06 (17%)**	**0.30 (83%)**
EH1	28.42	4.30 (15%)	24.12 (85%)
EH2	**0.39**	**0.05 (13%)**	**0.35 (90%)**
EH3	7.82	3.48 (45%)	4.34 (55%)
EH4	**0.99**	**0.55 (56%)**	**0.44 (44%)**
EH5	1.29	0.51 (40%)	0.78 (60%)
EH6	**0.37**	**0.07 (19%)**	**0.29 (78%)**
EH7	**0.74**	**0.44 (59%)**	**0.31 (42%)**
EH8	**0.75**	**0.41 (55%)**	**0.33 (44%)**
EH9	2.44	1.00 (41%)	1.45 (59%)
EH10	**0.44**	**0.12 (27%)**	**0.32 (73%)**

Table 7: Forecast error decomposition for the groups. Stable groups are denoted with bold values.

Table 7 presents the forecast error decomposition for each group. We can see that for each treatment the individual error is lower in stable groups. On average, the dispersion error accounts for less than 50 percent of the individual error. The dispersion error is also lower in EL compared to the other two treatments, thus suggesting that forecasts are more coordinated in EL. We test whether the difference in dispersion error between treatments is significant, and find that for F and EL the p-value is 0.230, using two-sided Kolmogorov-Smirnov test (all groups). For EL and EH, we find the difference to be significant at the 10 percent level ($p = 0.052$): The dispersion error accounts for a smaller share of the individual error in EL than in EH.

We also compute an alternative measure of coordination using the standard deviation of forecasts (computed as the median value for the last 40 periods), which we summarize

	groups									
	1	2	3	4	5	6	7	8	9	10
F	**0.20**	1.52	0.45	**0.31**	**0.27**	0.53	**0.21**	0.51	**0.35**	-
EL	**0.17**	0.72	1.06	**0.29**	**0.21**	0.26	0.31	0.44	0.60	**0.17**
EH	1.10	**0.17**	1.74	**0.42**	0.58	**0.20**	**0.25**	**0.26**	0.88	**0.21**

Table 8: Standard deviation of forecasts per group. Stable groups are denoted with bold values.

in Table 8. A Kolmogorov-Smirnov test confirms that there is no substantial difference across treatments. Therefore, we conclude that endogenous impacts do not lead to any significant differences in the coordination of forecasts. This leads us to the last formal result of our study.

Result 3. *Subjects highly coordinate their forecasts across all treatments.*

We confirm that a high level of coordination in forecasts is a robust and general feature of LtF experiments with positive feedback.

Finally, we investigate how subjects make forecasts by estimating a linear forecasting rule for each individual. We observe a general trend-following pattern in each treatment, with insignificant differences between treatments. Thus, endogenizing impacts does not seem to affect how subjects make forecasting decisions. In particular, subjects do not try to use their market impact to manipulate prices. Detailed results can be found in Appendix B.

5 Discussion

In this paper we extend the LtF asset-pricing experiment by allowing the subject impact on the market price to evolve endogenously, based on past forecast accuracy. Our environment captures some competitive features of financial markets where more successful fund managers attract more investors. The experimental design includes three treatments, which vary the importance of past forecast accuracy: (i) fixed impact (F), (ii) low sensitivity (EL) and (iii) high sensitivity (EH). Impacts evolve according to the discrete choice model while the sensitivity is captured by the intensity of choice parameter. This last parameter is important because it affects the number of influential forecasters in the market and therefore the degree of competition.

Our experimental results show that the effect of endogenous impacts depends on sensitivity to past forecast accuracy as well as on how stable the market is. When markets are stable, impacts with low sensitivity do not mitigate price dispersion but they do reduce mispricing by about two percentage points compared to the fixed-impact treatment. In unstable groups, we find a destabilizing effect: Price dispersion is significantly larger under high sensitivity than under fixed impacts. Overall, endogenizing impacts does not affect the number of stable markets.

The most crucial assumption of our study is that market impacts depend on forecasters' past performance. There is extensive evidence on how past performance by money managers predicts fund flows (see Agarwal et al., 2018). We assume that our myopic investors focus on short-term forecaster performance by using the last three periods.[25] If instead we used a longer time horizon, then our endogenous impacts would become equal because subjects highly coordinate their expectations and cumulative forecast errors are similar across all subjects. In contrast, considering a shorter time horizon could result in erratic behavior of market impacts.

Impacts could also be derived from (risk-adjusted) profits from trade rather than on forecast errors. De Long et al. (1990) show that market outcomes may be affected by the choice of performance measures. In our setup it is reasonable to use risk-adjusted profits as (mean-variance) investors care about risk in the asset-pricing model. Furthermore, Hommes (2001) demonstrates that forecast errors are equivalent (up to a constant) to risk adjusted profits. Therefore we expect our results to be robust with respect to other performance measures. Given the equivalence between risk adjusted profits and forecast errors, we prefer to employ the latter which consistently determines both subject impact and payoff.

Our design can easily be extended to study how endogenizing impacts affects a negative-feedback LtF experiment (e.g. the cobweb model), where the market price depends negatively on price expectations. Experimental findings using negative feedback show that subjects' forecasts converge quite fast to the rational expectations equilibrium price, even when the market price is driven by a single forecaster (Bao and Duffy, 2016). Hence, we expect endogenous impacts, which can reduce the level of competition, to produce similar results. Further work is needed to understand the role of performance in other, more complex environments, such as the asset-pricing model with two-period ahead forecasting or learning to optimize experiments, where —instead of forecasting the price— subjects directly decide how many assets to buy or how much to produce.

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[25]Greenwood and Shleifer (2014) finds that investor expectations depend strongly on most recent market experience. In a similar manner, we assume that the forecasters' recent performance matters more for market impacts.

proval 6592), and was supported by funds granted by Colby College, Hamilton College, University of Melbourne and Monash University. We are also grateful to John Duffy, Cars Hommes, Anita Kopányi-Peuker, and attendees of the BEAM-ABEE workshop at the University of Amsterdam for their insightful comments that help improve the manuscript. Dávid Kopányi and Jan Tuinstra acknowledge support from the ORA project "BEAM" (NWO 464-15-143) which is partly financed by the Netherlands Organization for Scientific Research (NWO).

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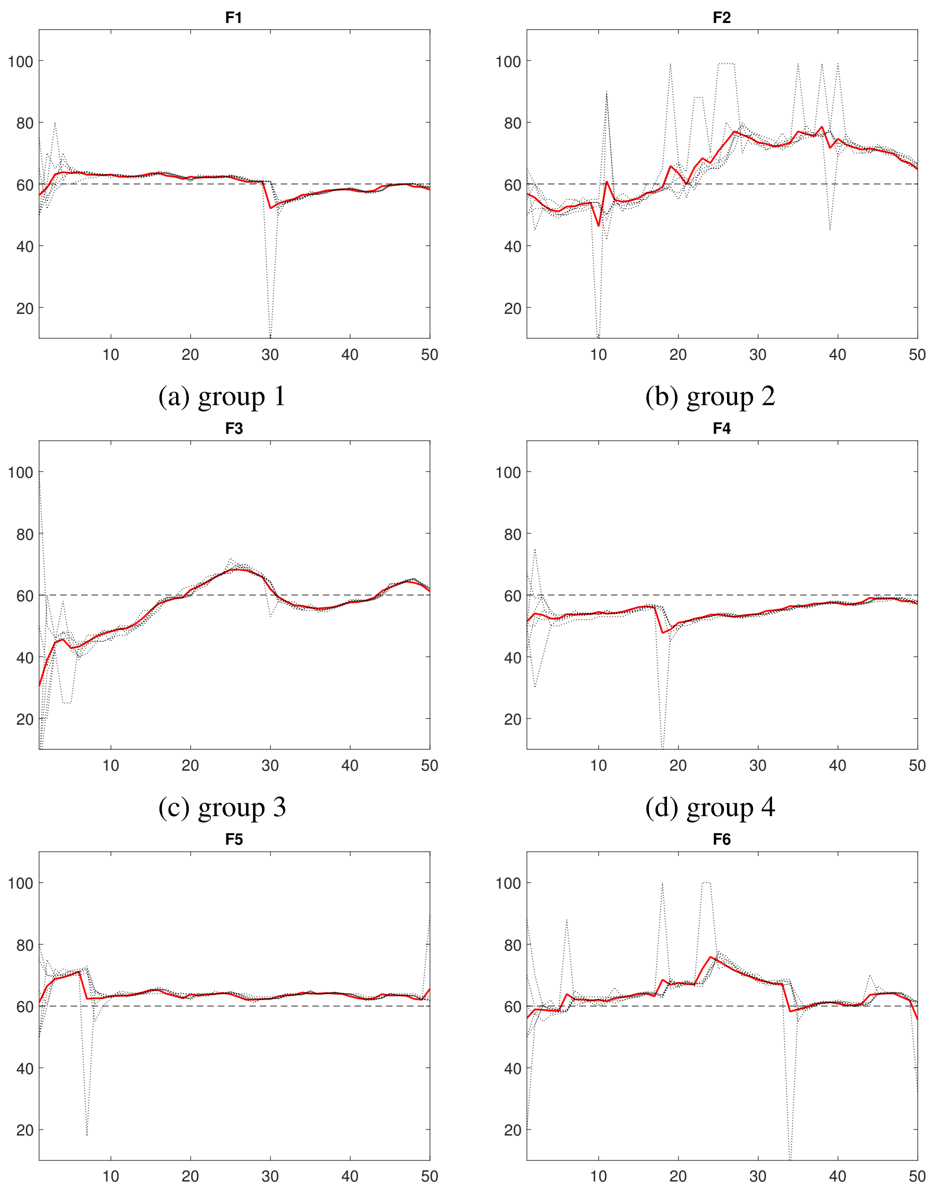
APPENDIX

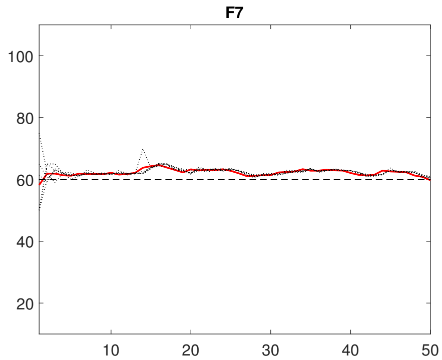
Appendix A. Time series of prices and impacts

Treatment *F*

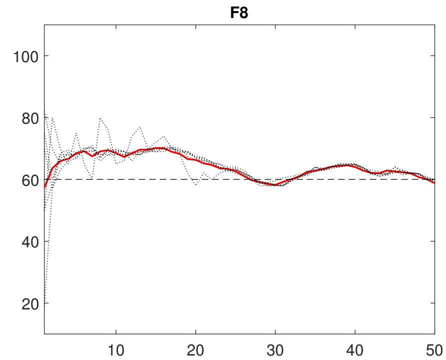


(a) group 1
(b) group 2
(c) group 3
(d) group 4
(e) group 5
(f) group 6

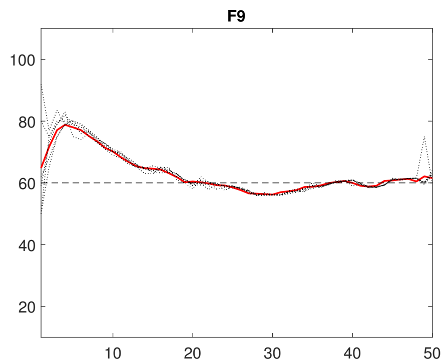
Figure 5: Time series of prices in treatment *F*, groups 1-6.



(a) group 7



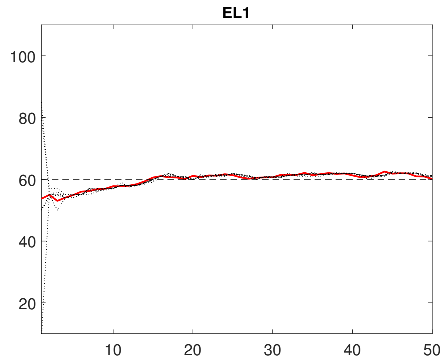
(b) group 8



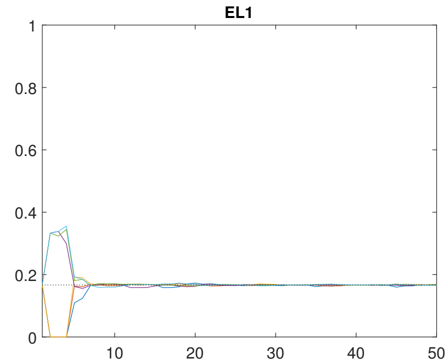
(c) group 9

Figure 6: Time series of prices in treatment *F*, groups 7-9.

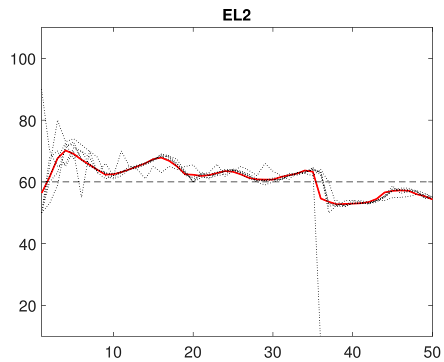
Treatment *EL*



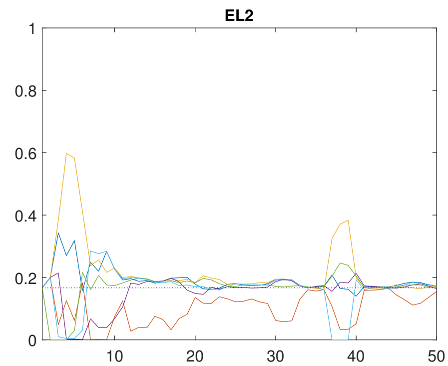
(a) price group 1



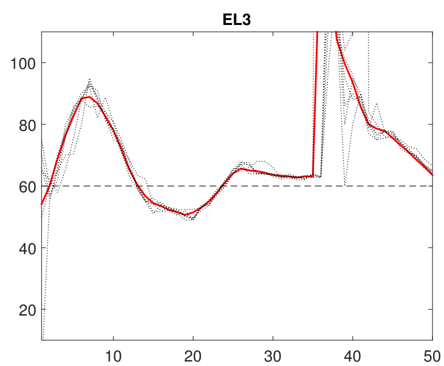
(b) impacts group 1



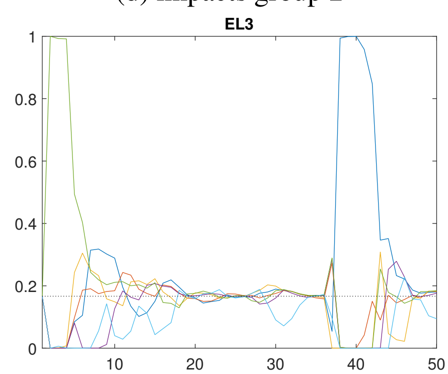
(c) price group 2



(d) impacts group 2

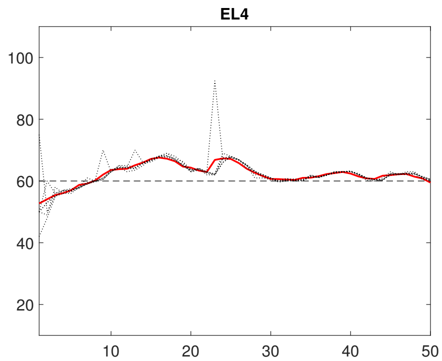


(e) price group 3

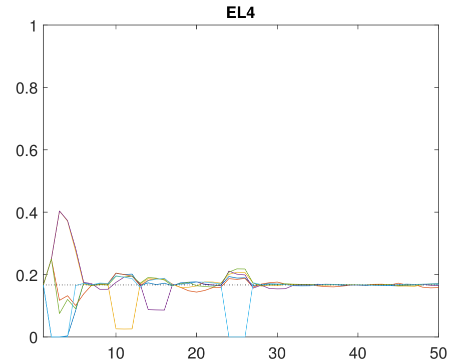


(f) impacts group 3

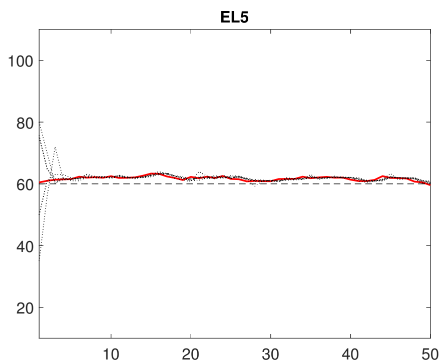
Figure 7: Time series of prices (left) and impacts (right) in treatment *EL*, groups 1-3.



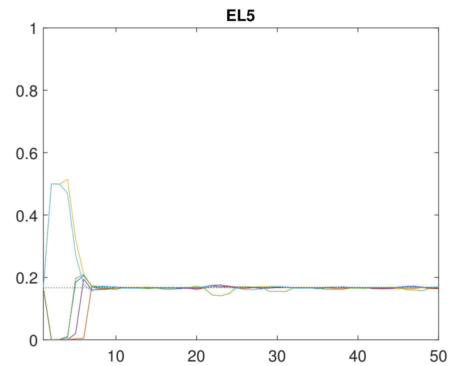
(a) price group 4



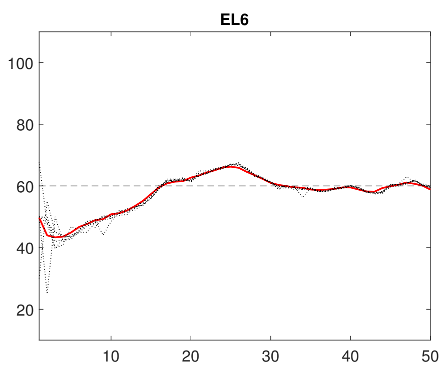
(b) impacts group 4



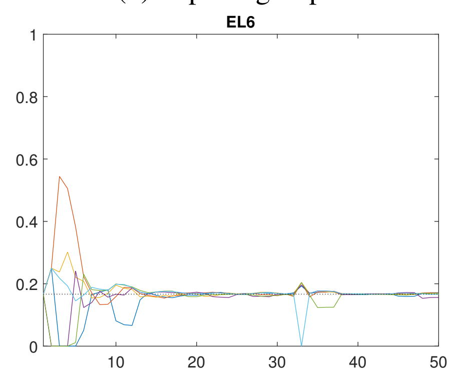
(c) price group 5



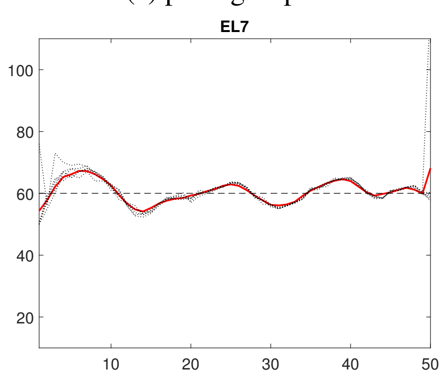
(d) impacts group 5



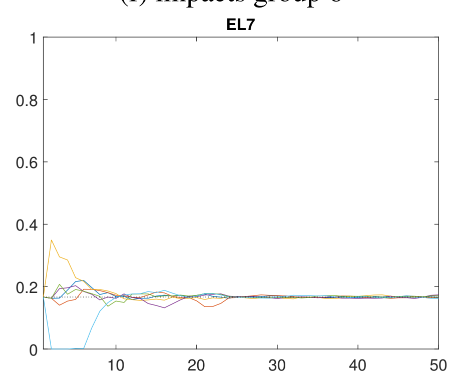
(e) price group 6



(f) impacts group 6

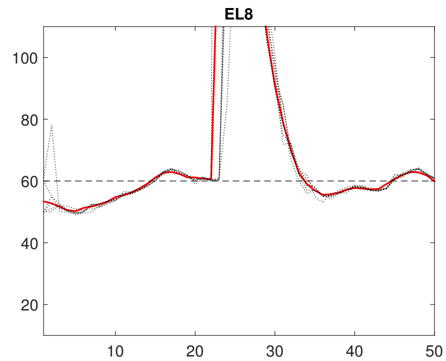


(g) price group 7

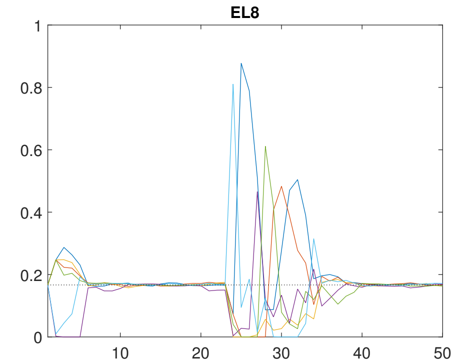


(h) impacts group 7

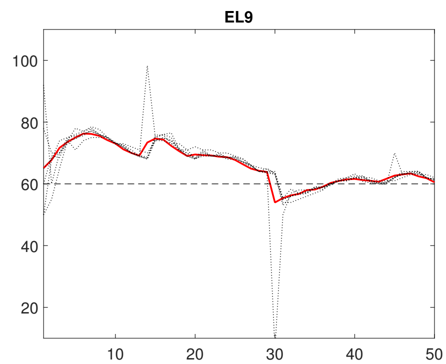
Figure 8: Time series of prices (left) and impacts (right) in treatment EL, groups 4-7.



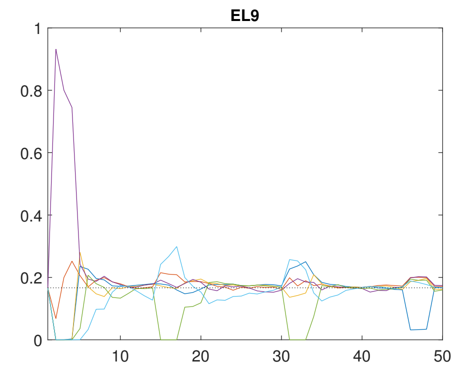
(a) price group 8



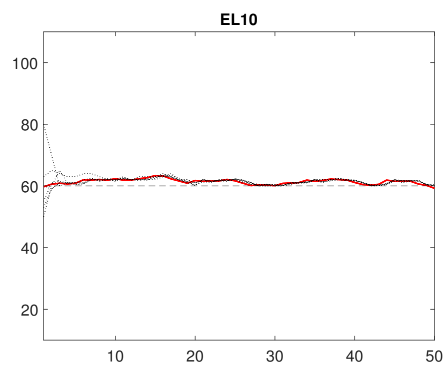
(b) impacts group 8



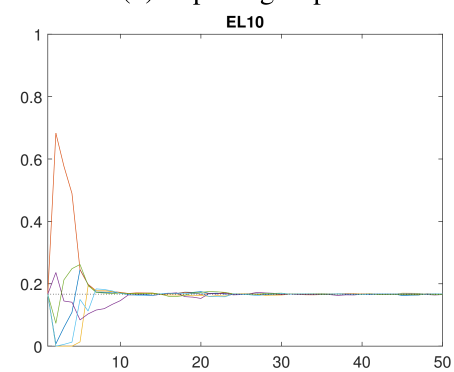
(c) price group 9



(d) impacts group 9



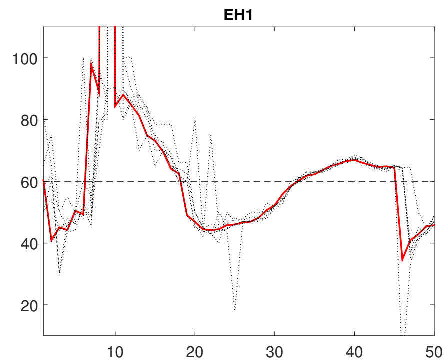
(e) price group 10



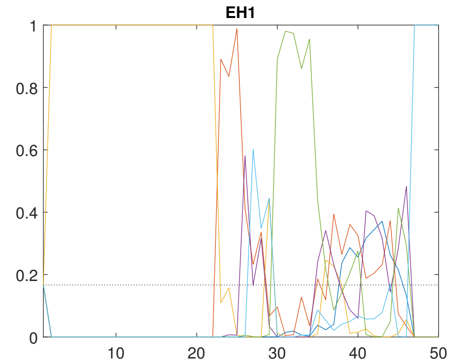
(f) impacts group 10

Figure 9: Time series of prices (left) and impacts (right) in treatment *EL*, groups 8-10.

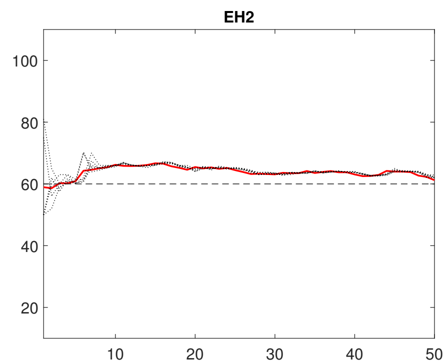
Treatment *EH*



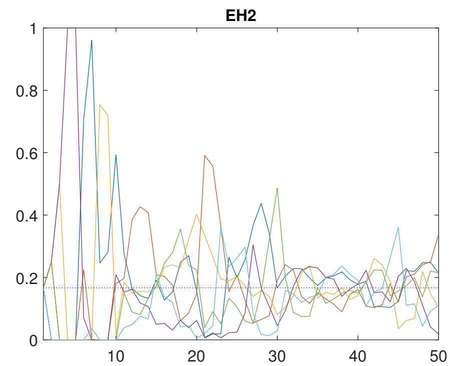
(a) price group 1



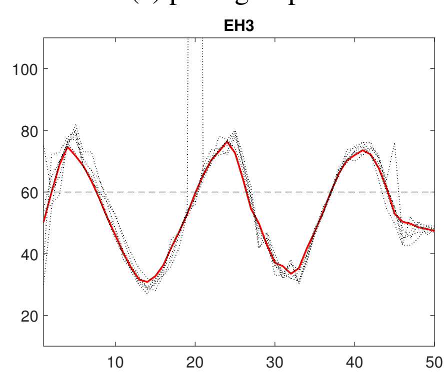
(b) impacts group 1



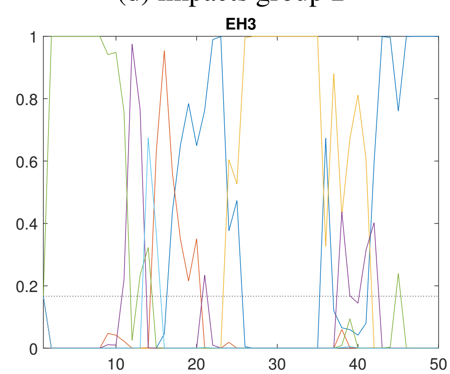
(c) price group 2



(d) impacts group 2

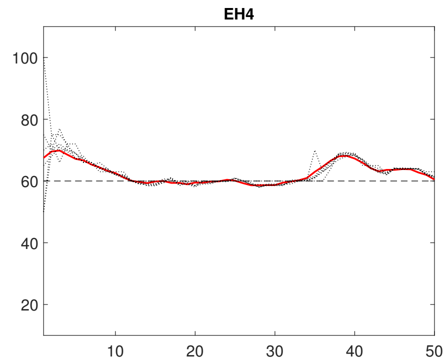


(e) price group 3

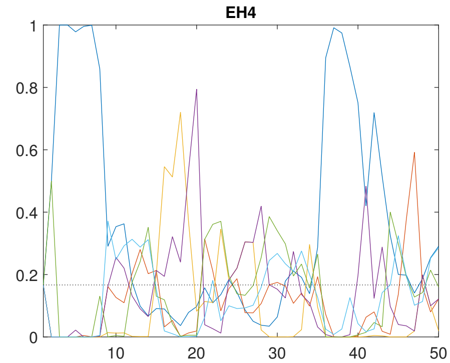


(f) impacts group 3

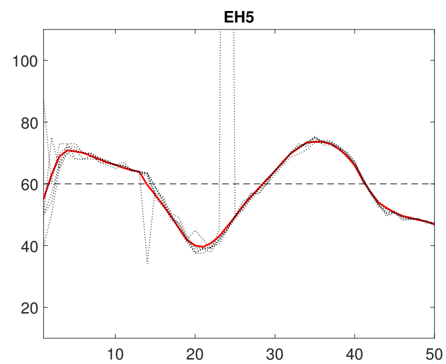
Figure 10: Time series of prices (left) and impacts (right) in treatment EH, groups 1-3.



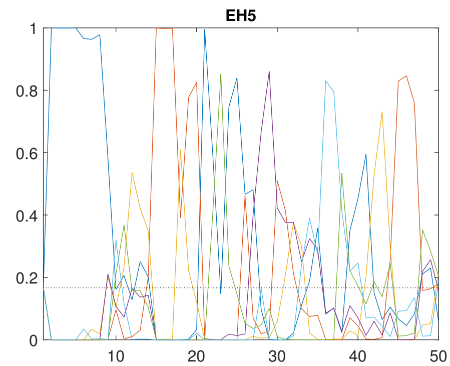
(a) price group 4



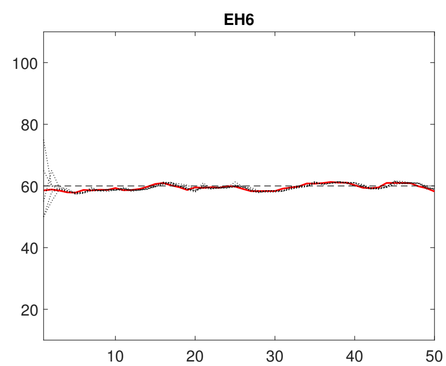
(b) impacts group 4



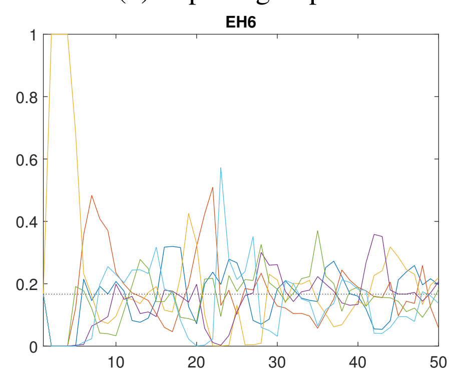
(c) price group 5



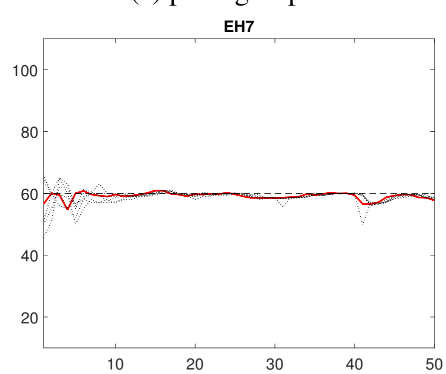
(d) impacts group 5



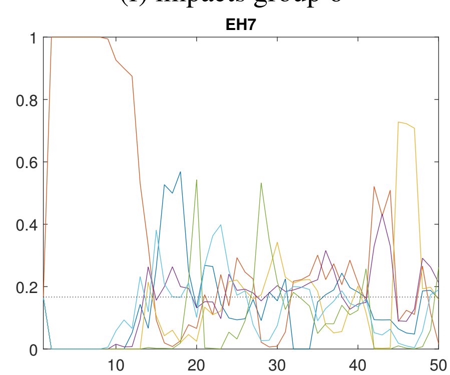
(e) price group 6



(f) impacts group 6

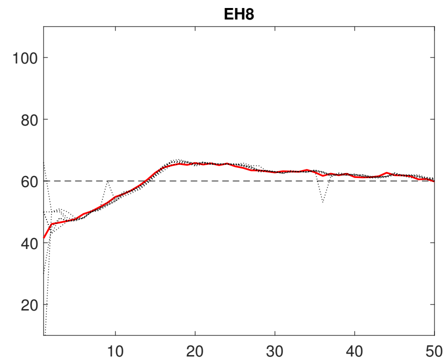


(g) price group 7

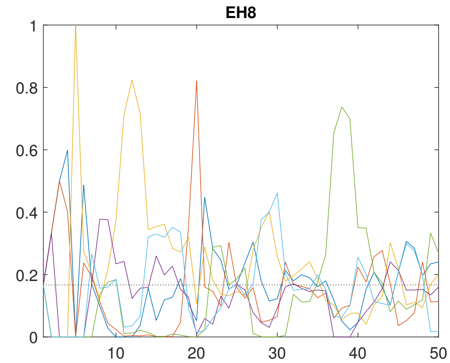


(h) impacts group 7

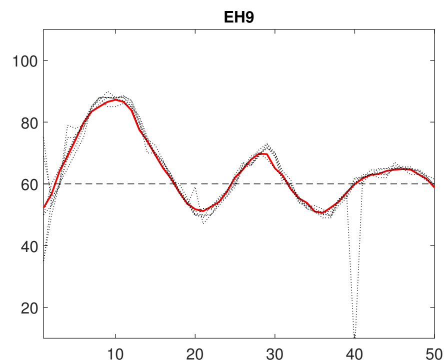
Figure 11: Time series of prices (left) and impacts (right) in treatment EH, groups 4-7.



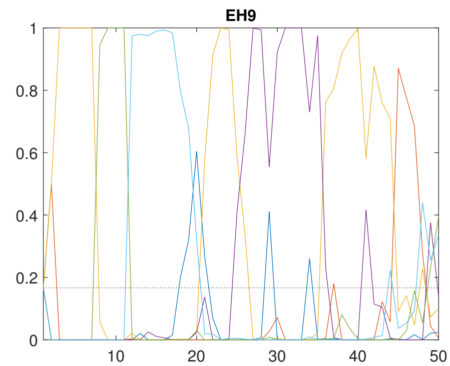
(a) price group 8



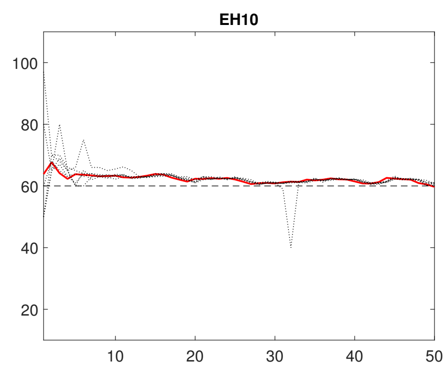
(b) impacts group 8



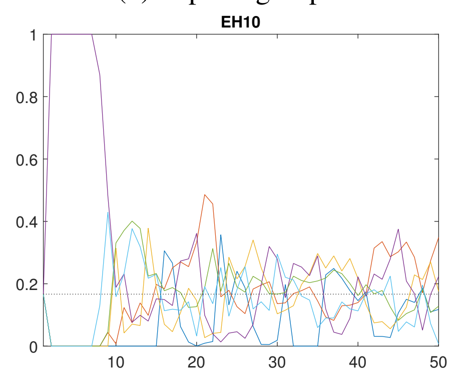
(c) price group 9



(d) impacts group 9



(e) price group 10



(f) impacts group 10

Figure 12: Time series of prices (left) and impacts (right) in treatment EH, groups 8-10.

Appendix B: Individual forecasting rules

For each subject h we estimate the following general forecasting rule, where the forecast for the next period depends on the last 4 realized prices and the subject's last 4 price forecasts:

$$p^e_{h,t+1} = \alpha + \sum_{k=0}^{3} \beta_k p_{t-k} + \sum_{k=0}^{3} \gamma_k p^e_{h,t-k} + \nu_t. \qquad (.5)$$

We apply stepwise linear regression to estimate the rules: All explanatory variables are included in the first regression and then the insignificant ones are removed one by one, starting with the most insignificant one. For estimating the decision rules we disregard data from the first 10 periods in order to account for potential initial learning. Also, we remove outlier forecasts from the analysis using the same rule as when analyzing coordination.

Table 9 summarizes the results of the regressions for all three treatments. The table shows the average parameter estimates per group as well as the averages over all groups, stable and unstable groups within the given treatment.[26] The estimations lead to 35 (64.8%), 36 (60%) and 40 (66.7%) good models, where (i) the residuals are not autocorrelated (Ljung-Box Q test), (ii) are not heteroskedastic (Engle's ARCH test) and (iii) there is no specification error (Ramsey's RESET test). In all three treatments the most commonly used variables are p_t, p_{t-1} and $p^e_{h,t}$. For 37% / 43.3% / 41.7% of the subjects these are the only significant regressors (besides the constant potentially).

Focusing on the average coefficients, we find the following general patterns in each treatment. For the stable groups p_t is most important variable, the other coefficients are much closer to 0 in absolute value. In unstable groups, the coefficient of p_{t-1} is larger in absolute value than in stable groups. The sum of the estimated coefficients of p_t and p_{t-1} is close to 1 in each treatments. This suggests that, on average, forecasting rules are close to the trend following rule $p^e_{t+1} = p_t + \theta(p_t - p_{t-1})$. Notice that θ corresponds to the opposite of the estimated coefficient of p_{t-1}. Therefore, our results show that subjects react more strongly to price changes in the unstable groups. We formally compare the trend following coefficients between treatments and based on the Kolmogorov-Smirnov test we do not find significant differences between treatments, even when focusing on the subset of stable and unstable groups separately. Thus, endogenizing impacts does not seem to affect how subjects make forecast. Our estimation results are in line with previous LtF experiments, see Section 4 of Bao et al. (2016).

[26] The coefficients of insignificant variables are set to zero when calculating average coefficients.

	C	p_t	p_{t-1}	p_{t-2}	p_{t-3}	p^e_t	p^e_{t-1}	p^e_{t-2}	p^e_{t-3}
F1	0.113	1.053	-0.03	0.1	0.006	0	-0.071	-0.061	-0.012
F2	3.377	1.047	-0.289	0.118	0	0.048	0.064	0	-0.055
F3	0.392	1.671	-0.663	-0.037	0	0.074	0	0	-0.06
F4	0.601	0.908	0.074	-0.036	-0.023	-0.008	0.056	0	0.013
F5	6.232	1.064	0.047	0.071	0	-0.057	-0.145	-0.06	-0.017
F6	0	1.083	-0.035	0	-0.052	0.006	0	0	-0.023
F7	2.195	1.084	0.04	0	0.048	-0.055	-0.085	-0.04	-0.017
F8	2.344	1.312	-0.565	-0.052	0.135	0.309	-0.034	-0.049	-0.078
F9	0	1.508	-0.516	0.061	-0.046	0	0.047	0	-0.056
all	1.695	1.192	-0.215	0.025	0.008	0.035	-0.019	-0.023	-0.034
stable	1.828	1.123	-0.077	0.039	-0.003	-0.024	-0.039	-0.032	-0.018
unstable	1.528	1.278	-0.388	0.007	0.021	0.109	0.008	-0.012	-0.054
EL1	8.504	0.81	0.027	0	0	0.082	0	-0.052	-0.018
EL2	0	1.288	-0.537	0.116	-0.084	0.065	-0.023	0.095	0.072
EL3	2.729	1.494	-0.729	0.124	-0.087	0.144	0	0.02	0
EL4	2.103	1.327	-0.23	-0.142	-0.069	0.104	-0.048	0	0
EL5	0	0.884	0.173	0.05	0	0.037	-0.18	0.03	0
EL6	-1.73	1.978	-0.763	0	0	-0.071	-0.056	0	-0.045
EL7	0.813	2.101	-1.1	0.052	0.031	-0.113	0	0	0
EL8	4.535	1.515	-0.635	0.278	-0.044	-0.046	-0.071	0.002	-0.089
EL9	1.672	1.048	-0.07	0	0.089	0.055	-0.025	-0.141	0
EL10	1.634	1.093	0	-0.067	-0.011	-0.075	0.042	0	-0.023
all	2.026	1.354	-0.387	0.041	-0.018	0.018	-0.036	-0.005	-0.01
stable	3.06	1.029	-0.008	-0.04	-0.02	0.037	-0.047	-0.006	-0.01
unstable	1.336	1.571	-0.639	0.095	-0.016	0.006	-0.029	-0.004	-0.01
EH1	1.614	1.163	-0.214	0	-0.143	0.148	-0.041	0.037	0
EH2	-0.85	0.975	0.027	0	0	0	0	0	0.02
EH3	3.255	1.604	-0.457	0	0	0.06	-0.122	-0.113	-0.033
EH4	0.07	1.315	-0.265	0	0.037	0.072	-0.043	-0.102	-0.042
EH5	1.368	1.7	-0.635	0	-0.095	0	0	0	0
EH6	0	1.292	-0.365	-0.092	-0.078	0.067	0.061	0.07	0.024
EH7	2.055	0.934	-0.047	0	-0.029	0.042	0	0	0.015
EH8	1.536	1.034	-0.217	-0.162	0	0.395	0	-0.079	0
EH9	1.164	1.645	-0.187	-0.333	0.072	-0.087	-0.095	-0.085	0.038
EH10	-0.867	1.08	-0.059	0.098	0.052	-0.101	-0.054	-0.004	0
all	0.934	1.274	-0.242	-0.049	-0.018	0.06	-0.029	-0.028	0.002
stable	0.324	1.105	-0.154	-0.026	-0.003	0.079	-0.006	-0.019	0.003
unstable	1.85	1.528	-0.373	-0.083	-0.041	0.03	-0.064	-0.04	0.001

Table 9: Average coefficients per group and over all, stable and unstable groups for each treatment.

Appendix C: Endogenous impacts instructions

Welcome! This is an economics experiment. If you pay close attention to these instructions, you can earn a significant sum of money. Each participant is paid $7 for attending. Throughout this experiment you can also earn points based on the decisions you make. The rate at which we exchange your points into cash will be explained to you shortly.

Please turn off your electronic devices, remain silent, and do not look at other participants' screens. If you have any questions, or need assistance of any kind, please raise your hand and we will come to you. If you disrupt the experiment by talking, laughing, etc., you may be asked to leave without compensation. We expect and appreciate your cooperation today.

General information

You are an advisor of a trader who is active on a market for a certain product. In each time period the trader needs to decide how many units of the product he will buy, intending to sell them again the next period. To take an optimal decision, the trader requires a good prediction of the market price in the next time period. As the advisor of the trader you will predict the price of the product during 50 successive time periods. Your earnings during the experiment will depend on the accuracy of your predictions. The smaller your prediction errors, the greater your earnings.

Your forecasting task

Your task is to forecast the price each time period as accurately as possible. At the beginning of each period, you will need to forecast the price for the current period. The information available to you will be the price in the preceding periods.

It is very likely that the price will be between 0 and 100 in the first period. After all participants have given their forecasts, the price is revealed and, based upon your forecasting error, your earnings for that period are calculated. Then the next period begins. This process continues for 50 time periods.

The available information for forecasting the price in period t consists of all past prices up to period $t-1$, your total earnings up to period $t-1$, and your past forecasts up to period $t-1$. Each period you will have limited time to make your forecasting decision. If you do not submit a forecast during this time frame, the trader you are advising will be inactive, and you will not earn any points in that given period. A timer will show you the remaining time for each period (1 minute for each of the first 10 periods, 45 seconds for each of the later periods).

Information about the market

The price of the product will be determined by the law of supply and demand. Supply and demand on the market are determined by the traders of the product. Higher price predictions make a trader demand a higher quantity. A high price prediction makes the trader willing to buy the product, a low price prediction makes him willing to sell it. There are six advisors active on this market, where each advisor corresponds to a participant to the experiment. Traders have a tendency to use the advice of advisors whose forecasts have been more accurate in the recent past. The effect that an advisor has on the market is therefore higher when his/her forecasts are more accurate because more traders will follow his/her advice. Furthermore, a number of small traders is active on the market that do not follow the advice of any of the advisors and they create small fluctuations in total supply and demand.

Earnings

Your earnings depend on the accuracy of your forecasts. Your payoff in period t is given by

$$\max[0, 1300(1 - \frac{1}{49} * error^2)]$$

where the error is the difference between realized market price and the forecasted price. The maximum possible points you can earn in each period (if you do not make a forecasting error) is 1300, and the larger your forecast error is, the fewer points you will make. Note, however, that you will never earn negative payoffs: If your forecast error in a particular period is very large, your payoff for that period will be zero.

We will pay you in cash at the end of the experiment based on the points you earned over the 50 rounds. You earn $1 for each 8125 points you make plus an additional $7 of show-up fee.